Environmental Pollution 225 (2017) 390–402

Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

Where do uncertainties reside within environmental risk assessments? Testing UnISERA, a guide for uncertainty assessment☆

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ARTICLE INFO

Article history:
Received 6 December 2016
Received in revised form
2 February 2017
Accepted 28 February 2017
Available online 8 March 2017

Keywords:
Uncertainty
Identification
Environmental
Risk
Assessment

ABSTRACT

A means for identifying and prioritising the treatment of uncertainty (UnISERA) in environmental risk assessments (ERAs) is tested, using three risk domains where ERA is an established requirement and one in which ERA practice is emerging. UnISERA's development draws on 19 expert elicitations across genetically modified higher plants, particulate matter, and agricultural pesticide release and is stress tested here for engineered nanomaterials (ENM). We are concerned with the *severity* of uncertainty; its *nature*; and its *location* across four accepted stages of ERAs. Using an established uncertainty scale, the risk characterisation stage of ERA harbours the highest severity level of uncertainty, associated with estimating, aggregating and evaluating expressions of risk. Combined epistemic and aleatory uncertainty is the dominant nature of uncertainty. The dominant location of uncertainty is associated with data in problem formulation, exposure assessment and effects assessment. Testing UnISERA produced agreements of 55%, 90%, and 80% for the severity level, nature and location dimensions of uncertainty between the combined case studies and the ENM stress test. UnISERA enables environmental risk analysts to prioritise risk assessment phases, groups of tasks, or individual ERA tasks and it can direct them towards established methods for uncertainty treatment.

1. Introduction

Uncertainties, if left unaddressed within environmental risk assessments (ERAs; Pollard et al., 2002; Defra, 2011) can lower stakeholder confidence in expressions of risk, weaken the basis for risk management and delay well-founded decisions whilst uncertainties are considered and then treated. Risk analysts recognise ERAs should consider uncertainty (Costanza et al., 1992; Linkov and Burmistrov, 2003; Dale et al., 2008; European Environment Agency, 2007; Funtowicz and Ravetz, 1990; Handmer et al., 2001; Hart et al., 2007; Refsgaard et al., 2007; Linkov et al., 2014) and the conventional means for this, 'uncertainty analysis', seeks to support proportionate expressions of risk estimates, to inform system understanding and lend confidence to the identification of risk management options. Uncertainty, as envisaged by practitioners devising tools for its management, can be investigated through the dimensions of its *location* (where the uncertainty is manifest within the various phases of an ERA); its *nature* (the incompleteness of knowledge, or inherent variability of natural systems), and its *severity level* (ranging from determinism to complete ignorance; Walker et al., 2003). A primary tool for risk analysts has been the uncertainty typology (Knol et al., 2009; Morgan et al., 1990; van Asselt and Rotmans, 2002), though its variable implementation by practitioners has resulted in its inconsistent use (Gillund et al., 2008; Knol et al., 2009; Sigel et al., 2010).

Our aim is to assemble comprehensive, research-informed insight for risk analysts, through testing an uncertainty identification system (UnISERA); helping risk analysts design and perform ERAs with uncertainties more firmly in mind. In this study, ERA comprises the four phases of problem formulation, including hazard identification (framing, conceptual model development and hazard identification); exposure assessment (dose); effects assessment (consequences) and risk characterisation (risk significance) as communicated in Skinner et al. (2016). Our study objectives were to extend a 'proof of concept' approach (Skinner et al., 2016) by testing it across a range of environmental hazards (risk domains); and then stress test it with an emerging risk where data was particularly sparse. In doing so, we sought to evaluate the general applicability of UniSERA to a range of environmental risks.

☆ This paper has been recommended for acceptance by B. Nowack.

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http://dx.doi.org/10.1016/j.envpol.2017.02.065

2. Materials and methods

In this study, we were interested in the extent to which categories of uncertainty were generalizable across different risk domains; and we sought to test this for environmental hazards where ERA was established and then 'stress test' our approach for an emerging risk (Fig. 1). We deployed the evaluation, by experts, of three dimensions of uncertainty (severity, nature, location) across three risk domains ('test' case studies) and one emerging risk case study used to stress test our approach. Three domains on which to test UnISERA were; ones: (a) that had substantive empirical evidence to allow risk-informed decisions; (b) where ERAs were used widely to guide risk management decisions; and (c) where substantive uncertainty was reported. For each, an evidence base of peer-reviewed ERAs was compiled from Scopus™. Research papers were assessed for relevance using criteria (a) to (c) above, for: (1) genetically modified higher plants; (2) atmospheric particles; and (3) pesticides in surface waters. A fourth emerging risk, engineered nanomaterials (ENM), was used to stress-test the wider applicability of UnISERA. For each ERA and risk domain, a dominant risk relationship containing a stressor (a hazard) and a source-pathway-receptor (S-P-R) relationship (Pollard et al., 2002) was identified for onward uncertainty identification and analysis. To allow comparisons across the test case studies an ERA protocol – an explicit list of tasks required to complete an ERA - was created for each S-P-R relationship which was then validated by experts sourced from their peer-reviewed research (see Skinner et al., 2016; Table S1). Experts' opinions on uncertainties within these ERA tasks were compiled for the *severity* level, *nature*, and *location* of uncertainties for each domain, so creating UnISERA, a means of guiding risk analysts on the sources of uncertainty across the phases of an ERA. Stress-testing UnISERA against ENM followed; a domain that purposefully differed from the previous three by its paucity of empirical evidence, allowing claims to be examined for UniSERA's general applicability.

Metrics, on experts' opinions on the location, nature and severity level of uncertainties within ERAs, were compared using measures of central tendency. The central tendency and spread of data in the severity level (of uncertainty) dimension deployed median values and inter-quartile ranges (IQRs). Parametric (e.g. mean and standard deviation, two-sample *t*-test or ANOVA) or non-parametric (e.g. median and inter-quartile range, Mann-Whitney or Kruskal-Wallis) tests deployed SPSS v19 (SPSS Inc., Chicago IL). Metrics were developed for: (a) individual tasks that comprised the case study specific ERAs; (b) groups of tasks in the ERA; (c) the main phases of the ERA; and (d) on an overall basis. Agreement between opinions was deemed secure where median values were within the same uncertainty *category* of either: determinism (at a level of 0.0); statistical uncertainty (0.1–3.3); scenario uncertainty (3.4–6.6); ignorance (6.7–9.9); or total ignorance (10.0). To avoid two data-points being similar, yet expressed in different categories (e.g. 3.0 and 3.5, above), agreement was restricted to a difference of no more than 1.0 (i.e. 10% of a zero to 10 scale) between corresponding values. Three nature of uncertainty categories (epistemic, aleatory and 'combined') and seven location of uncertainty categories were compared with the corresponding values in the ENM case study. These tests allowed an examination of the distribution of uncertainties across the case study ERAs (graphical abstract). Our findings illustrate the extent to which uncertainties are common to ERAs across a diverse set of risks, allowing an evaluation of, and claims for the broad applicability of UnISERA.

3. Results

3.1. Generic and case study ERA templates

The generic ERA 'template' of tasks is published (Skinner et al., 2016). Table S1 (Supporting Information) lists its 105 tasks, organised by ERA phase, sub-phase, and task group; with individual tasks that did *not* feature for the three case studies shown in grey for completeness. For the case studies used to test UniSERA, a rigorous appraisal of ERAs from the literature was required because the assembly of UniSERA and its assessment of broader applicability rests on a comparison of experts' views on the categorisation of uncertainties across range of risk domains.

For case study 1, genetically modified higher plants, a literature search returned 155 peer-reviewed articles, from which an evidence base of 118 articles explicit about risk was formed (Table 1). The most frequently cited risk relationship was the potential for *Bacillus thuringiensis* (Bt)-modified maize (*Zea mays*) to impact on non-target Lepidoptera. Of 19 articles, thirteen (Anderson et al., 2005; Dively et al., 2004; Gathmann et al., 2006; Hansen Jesse and Obrycki, 2000; Hellmich et al., 2001; Losey et al., 1999; Mattila et al., 2005; Oberhauser et al., 2001; Perry et al., 2010; Sears et al., 2001; Stanley-Horn et al., 2001; Wolt et al., 2003; Zangerl et al., 2001) specified larvae of the Monarch butterfly (*Danaus plexippus* L.) as the receptor of interest. Thereby, 'potential

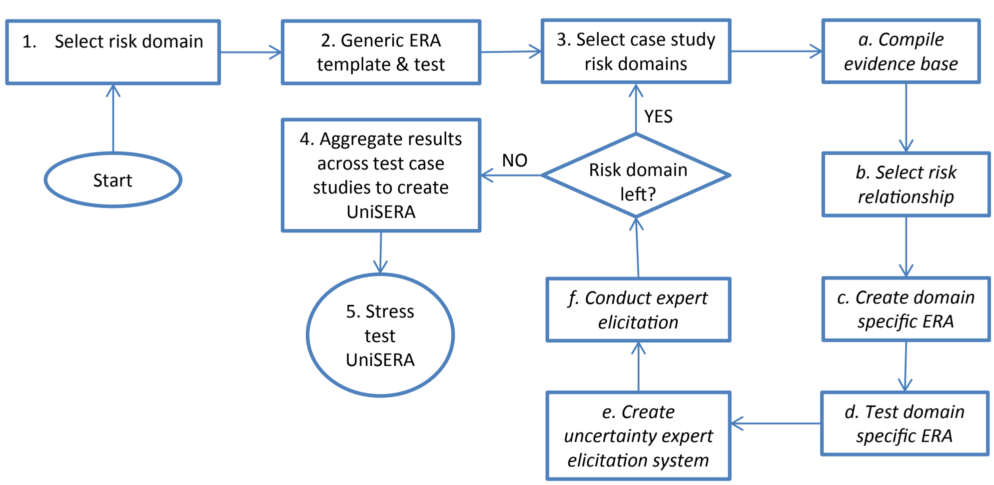

Fig. 1. Approach for testing and stress-testing UnISERA using four ERA case studies.

Table 1
Summary characteristics for eliciting the identification of uncertainties for each test case study and for the stress test ENM case study.

Abbreviated case study title and number	Evidence base			Features of uncertainty identified from the case studies across four risk assessment phases						
	Peer reviewed articles sourced	No. articles in case study evidence base	Risk relationship cited (n) times for the receptor of interest	Uncertainty experts and their sectors (n) participating in the elicitation	Experts' country of origin	Experts (n) in uncertainty assessment	**Problem formulation** tasks (n) assessed	**Exposure assessment** tasks (n) assessed	**Effects assessment** tasks (n) assessed	**Risk characterisation** tasks (n) assessed
1. 'GM higher plants'	155	118	13	a2; i1; r2	Ger; SA, UK; USA	5	27	28	16	11
2. 'Particles'	160	61	19	a2; r3	UK; USA	5	26	29	16	11
3. 'Pesticides'	127	49	5	a3; i1; r5	Can; Fr; Gre; Neth; Spain; Switz; UK	9	31	36	21	14
Stress test. 'Engineered nanomaterials'	84	50	(26)	a3; r3	Lux; Swe; Neth; UK; US	6	30	35	20	14

Bacillus thuringiensis (Bt) modified maize (*Zea mays*) risk to non-target Monarch butterfly larvae' was the case-specific risk relationship proposed. Thirteen articles for this S-P-R relationship informed development of a case-specific ERA process (version 1 of a risk assessment template), which was validated by 7 experts from the evidence base, creating a version 2 template. Five experts participated in the elicitation (Skinner et al., 2016) (Table 1), assessing 82 ERA-based tasks (27 in problem formulation, 28 in exposure assessment, 16 in effects assessment, and 11 in risk characterisation) for the severity levels, natures, and locations of uncertainty using the scales described by (Skinner et al., 2016). Experts from academia (a, n = 2), industry (i, n = 1), and regulation (r, n = 2) resided in Germany (n = 2), South Africa, the UK and the US. As an overview, the median severity level of uncertainty across all tasks in case study 1, on the 0 to 10 scale above, was 3.4. The nature-based aspect of uncertainty with the highest median occurrence was the 'combined' category (60% occurrence), whilst the location-based uncertainties of 'data' and 'variability' dominated, with overall medians of 60%.

For case study 2, atmospheric particles, the literature returned 160 peer-reviewed articles (Table 1) with 61 forming the evidence base. The S-P-R relationship (Allen et al., 2009; Betha and Balasubramanian, 2011; Boldo et al., 2011; Brook et al., 2011; Díaz and Rosa Dominguez, 2009; Deck et al., 2001; Goswami et al., 2002; Greco et al., 2007; Greene and Morris, 2006; Jiménez et al., 2009; Laden et al., 2000; Lai et al., 2004; Martonen and Schroeter, 2003; Orru et al., 2011; Post et al., 2001; Saldarriaga-Noreña et al., 2009; Sullivan et al., 2003; Symons et al., 2006; Tainio et al., 2010) was 'potential ambient outdoor $PM_{2.5}$ risk to human health'. The median severity level of uncertainty across case study 2 was 5.0, the median occurrence rate for the combined nature category 100% and the most frequently occurring locations for uncertainty were data, variability and model uncertainty with median rates of 80%.

Case study 3, an original proof of concept for UniSERA applied to pesticide impacts in surface waters, is published (Skinner et al., 2016) with the S-P-R relationship identified as 'potential agricultural chemical pesticide risk to surface water organisms'. The case study median severity level of uncertainty was 4.0, between the comparable values in case studies 1 and 2. Experts consistently communicated the uncertainty was a combination of epistemic and aleatory in nature, similar to the other case studies. Whilst 'data' was the joint-highest location-based uncertainty in case studies 1 and 2, here it was the standalone highest with a median rate of 67%.

3.2. Assembling UnISERA

Next, expert responses (n = 19 in total; row 6, Table 1) for the first three test case studies were aggregated using equal weights to form UnISERA; describing the severity levels, natures, and locations of uncertainty across 89 ERA-based tasks (Fig. 2a–d for severity; Table 2 for nature and location; cross refer to Table S1 for ERA task group column). Results are reported for the four phases of ERA: problem formulation, exposure assessment, effects assessment and risk characterisation.

Overall, the median severity level of uncertainty across 89 tasks was 4.0, at the lower end of scenario uncertainty. There were no individual tasks across the four phases for which either epistemic or aleatory uncertainties (nature) contained a higher median occurrence than when combined (Table 2).

In terms of the location in which uncertainty was manifest, data uncertainty was the primary concern, with median

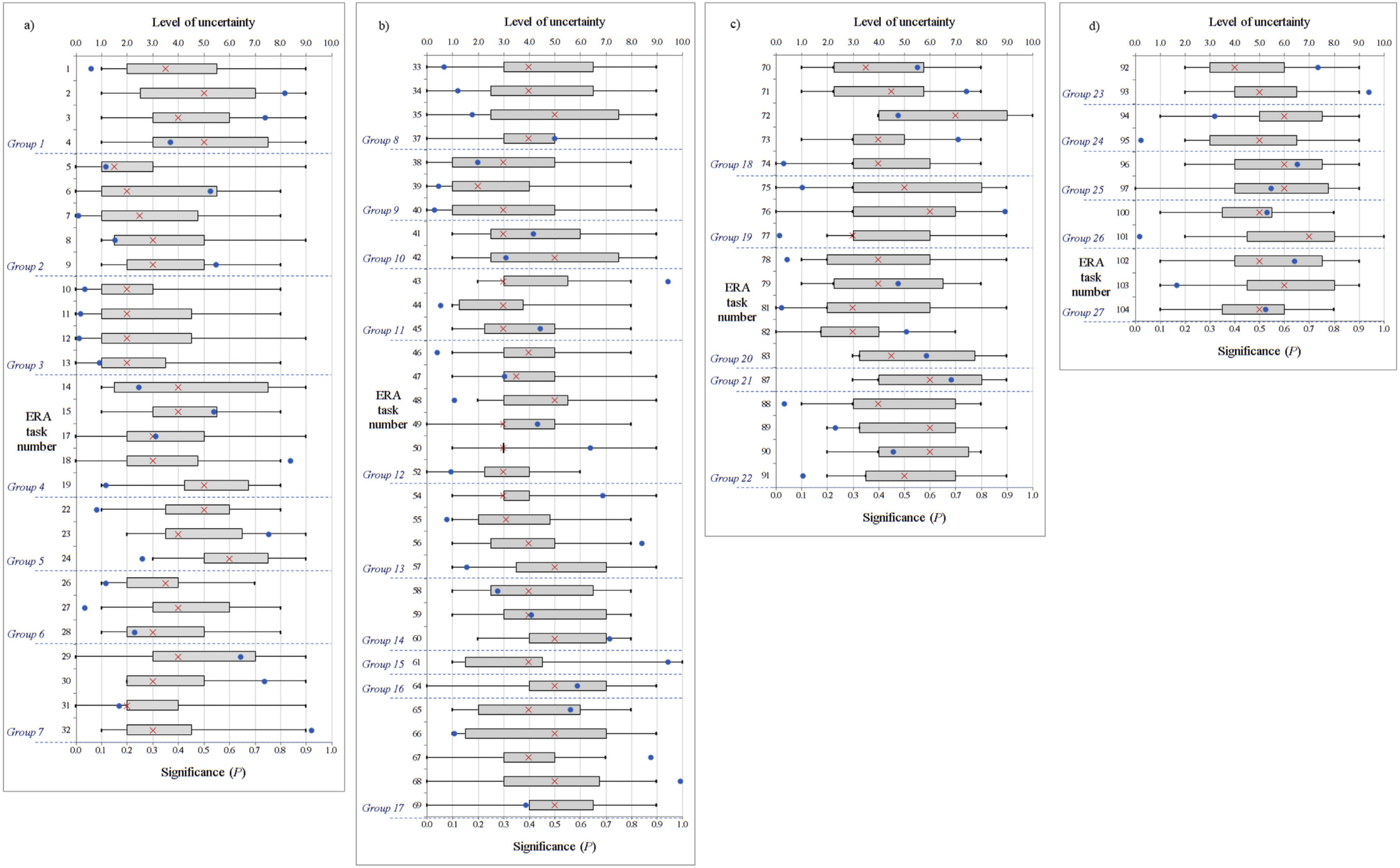

Fig. 2. a–d. The aggregated severity of uncertainty, communicated by experts (n = 19) in the first three test case studies, across 89 assessed ERA tasks and organised into the ERA phases of 2a) problem formulation, 2b) exposure assessment, 2c) effects assessment and 2d) risk characterisation. Described using median values (red crosses), inter-quartile ranges (boxes), and low-high range values (dashed lines) on a 0 (representing determinism) to 10 (representing total ignorance) scale. The statistical significance (P; $\alpha = 0.05$) of the central tendencies, tested using Kruskal-Wallis (or Mann-Whitney for ERA tasks with two datasets), are shown (blue circles). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Median occurrence rates (%) for the nature and location of uncertainty across three case studies as provided by experts (n = 19) in UnISERA, by ERA phase (modal values included for comparison).

ERA phase	Nature of uncertainty (%)			Location of uncertainty (%)						
	Epistemic	Aleatory	Combined	Data	Language	System	Variability	Extrapolation	Model	Decision
Problem formulation median	21	5	66	63	16	53	45	37	45	24
Problem formulation mode	11	5	74	68	16	63	42	26	53	26
Exposure assessment median	21	16	55	63	5	36	58	37	32	15
Exposure assessment mode	21	16	53	63	0	32	68	37	26	11
Effects assessment median	12	8	73	68	5	32	62	49	50	11
Effects assessment mode	11	5	74	74	5	32	32	53	47	5
Risk characterisation median	5	11	84	53	11	47	58	68	58	37
Risk characterisation mode	5	11	84	47	5	53	68	68	68	47
Overall median	19	11	65	62	11	42	55	42	45	21
Overall mode	11	5	74	68	5	53	68	47	53	11

occurrences of at least 50% in 69 out of 89 tasks, followed by variability (57 out of 89), system (35), model (35), extrapolation (29), decision (2), and language (0). Uncertainty is most severe in the latter two phases of ERA (Fig. 2c and d; Table 2). The median aggregated severity level of uncertainty for effects assessment was 4.3 (Fig. 2c), which had the lowest degree of expert agreement across its constituent phases, with a median IQR of 3.8. Data uncertainty was the most frequently occurring location of uncertainty, returning its highest median value at 68% (Table 2). Variability featured in effects assessment to its highest extent, at 62%. Risk characterisation yielded a median severity level of uncertainty of 5.0 (Fig. 2d), higher than the other phases. Groups 25 ($P = 0.41$), aggregating risk estimates; and 26 ($P = 0.09$), assessing the confidence in risk levels, contained the highest level (6.0).

The combined nature category reported its highest phase-by-phase occurrence rate, with a median value of 84% (Table 2). Extrapolation uncertainty expressed the highest associated median occurrence rate (68%), followed by variability and model uncertainties (both 58%; Table 2). The extrapolation location was high for the group of tasks associated with estimating risk magnitude (group 24; 82%), whilst the model location featured most heavily in the subsequent group, which concerned aggregating those risk levels (group 25; 68%).

3.3. *Stress-testing UnISERA*

How does UnISERA perform when stress-tested for an emerging risk, compared to the established risk domains used to construct UnISERA? For the ENM case study, the literature returned 84 peer-reviewed articles, from which an evidence base of 50 was formed (Table 1). These articles were identified based on the criteria in Section 2 drawing on the published literature at the time of the study (end of 2011/2012). We recognise the evidence base may not encompass more recent publications in this area; however, we believe there is sufficient data in the study to stress test our approach. ENMs are an emerging risk and, at the time of this research, most papers did not focus on specific sources, stressors, pathways or receptors.

The most frequently occurring aspects within the evidence base were used to create a risk relationship, with information drawn from the section(s) of the corresponding articles. These were consumer-based engineered nanomaterials for the source (n = 20) (Aschberger et al., 2011; Biskos and Schmidt-Ott, 2012; Chio et al., 2012; Farkas et al., 2011; Gottschalk et al., 2010; Handy et al., 2008; Johnson et al., 2011; Lapresta-Fernández et al., 2012; Lorenz et al., 2011; Madl and Pinkerton, 2009; Matranga and Corsi, 2012; Musee et al., 2010; Musee, 2011; Mueller and Nowack, 2008; Olson and Gurian, 2012; Shaw and Handy, 2011; Som et al., 2011; Thomas et al., 2009, 2011; Wang et al., 2011) nanosilver for the stressor (n = 8) (Aschberger et al., 2011; Chio et al., 2012; Farkas et al., 2011; Gottschalk et al., 2010; Lapresta-Fernández et al., 2012; Lorenz et al., 2011; Mueller and Nowack, 2008; Musee, 2011) and freshwater fish for the receptor (n = 16) (Aschberger et al., 2011; Chen et al., 2011; Chio et al., 2012; Eckelman et al., 2012; Farkas et al., 2011; Griffitt et al., 2008; Handy et al., 2008; Johnson et al., 2011; Lapresta-Fernández et al., 2012; Matranga and Corsi, 2012; Quik et al., 2011; Shaw and Handy, 2011; Thomas et al., 2011; Wang et al., 2011; Zhu et al., 2007, 2008) yielding a S-P-R relationship of ‘potential consumer-based engineered nanomaterials risk to freshwater fish’, with a collective pool of 26 ERAs, or ERA sections.

Twenty-six articles were used to form the ERA template version 1, validated by 9 ENM experts, creating version 2. Six experts participated in the uncertainty elicitation (Table 1), assessing 99 ERA-based tasks for the severity levels, natures (Fig. 3a–d; Fig. 4a–c) and locations of uncertainty (for brevity in Fig. S1a–g). The median severity level of uncertainty across all 99 tasks in the ENM case study was 5.0, the combined nature category being dominant with a median occurrence rate of 67% and the location-based source of data uncertainty the primary concern for experts (83%), followed by system and variability (both 50%).

For the stress test, 87 of the 89 combined case study ERA tasks (first three case studies used to construct UnISERA) were compared against corresponding tasks in the ENM stress test case study (Fig. 3a–d). Two tasks (Table S1; Tasks 38 and 50) did not feature in the ENM case study and were not compared. Fig. 3a–c presents the extent of agreement between the aggregated case study metrics for UnISERA and the ENM stress test case study for four phases of ERA. Fig. 4a–c compares the nature of uncertainty categories across the 27 groups of ERA tasks (Table S1).

The median severity level of uncertainty in risk characterisation was 5.0. Risk characterisation recorded the highest level of similarity of the four phases (Fig. 3d), with 10 out of 11 tasks agreeing (91%). Four of the five groups in this phase had agreement levels of 100%, namely groups 23 ($P = 0.75$), 24 ($P = 0.16$), 25 ($P = 0.12$), and 27 ($P = 0.32$). The difference in median occurrence rates was lower for the nature dimension in this phase than any other, at 11% (Fig. 4). Risk characterisation yielded a median agreement in 9 out of 11 tasks (82%) for the location dimension (Fig. S1). Language and decision uncertainty both returned an agreement of 100%, with model uncertainty agreeing in just 18% of cases (2 out of 11 tasks).

In contrast, the median severity level of uncertainty for exposure assessment in the ENM case study was 6.0, compared with 4.0 for the combined case studies. Exposure assessment yielded the lowest severity level of agreement (Fig. 3b), with 8 out of 30 tasks agreeing (27%). Of the seven groups across the four ERA phases that were in complete disagreement (i.e. all tasks within the group disagreed), six were found in exposure assessment, namely groups 9 ($P = 0.01$), 11 ($P = 0.00$), 14 ($P = 0.00$) 15 ($P = 0.02$), 16 ($P = 0.02$),

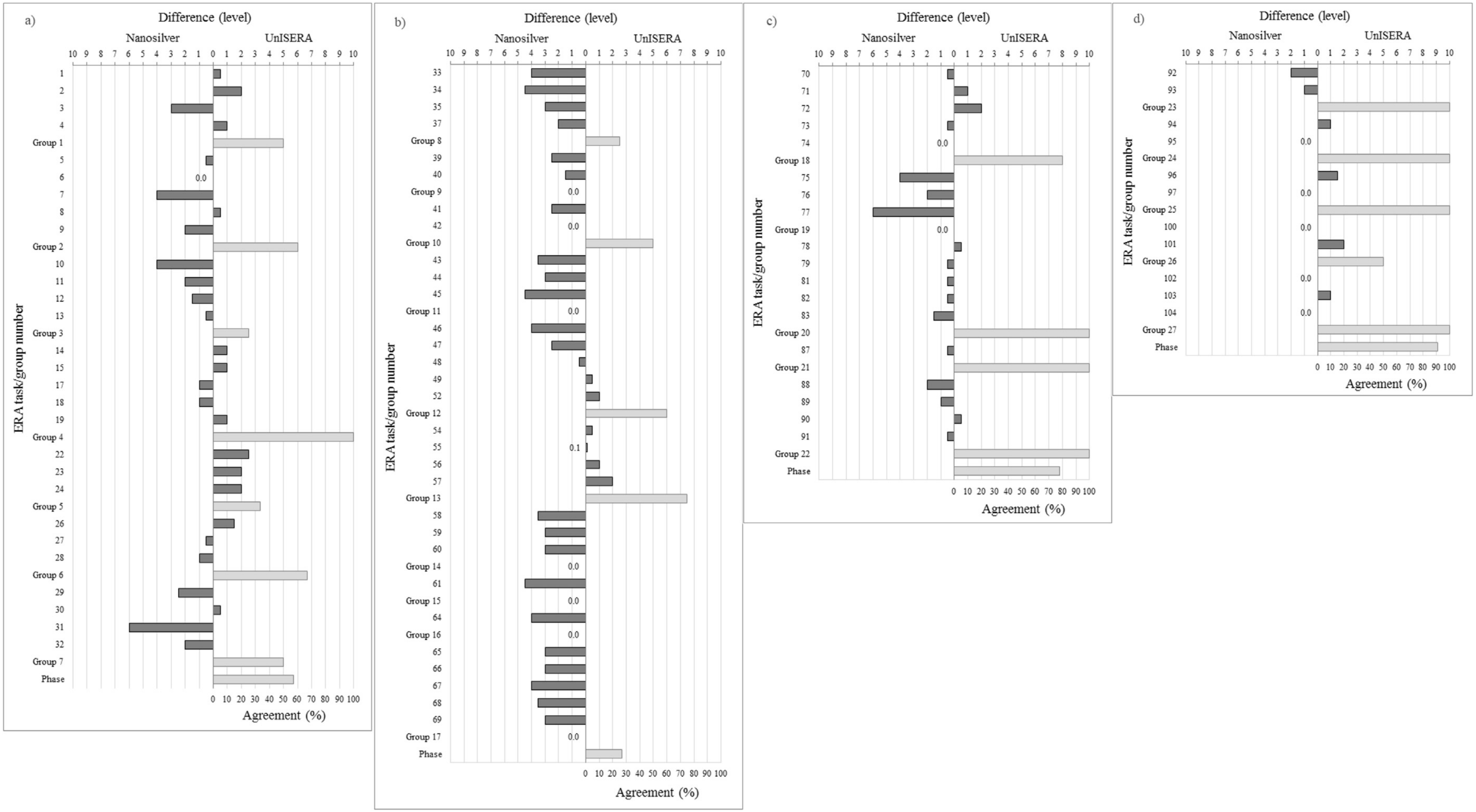

Fig. 3. a–d. A comparison of the levels of uncertainty communicated in the stress test ENM case study and UnISERA, organised by the ERA phases of a) problem formulation, b) exposure assessment, c) effects assessment, and d) risk characterisation, where: the upper horizontal axis shows the difference across the 87 assessed ERA tasks (dark grey bars starting at the central vertical axis and expanding left for higher nanosilver levels or right for higher UnISERA levels), on a 0 (representing determinism) to 10 (representing total ignorance) scale; the lower horizontal axis shows percentage agreement across the ERA tasks, for the 27 groups of tasks and overall for the four ERA phases (light grey bars).

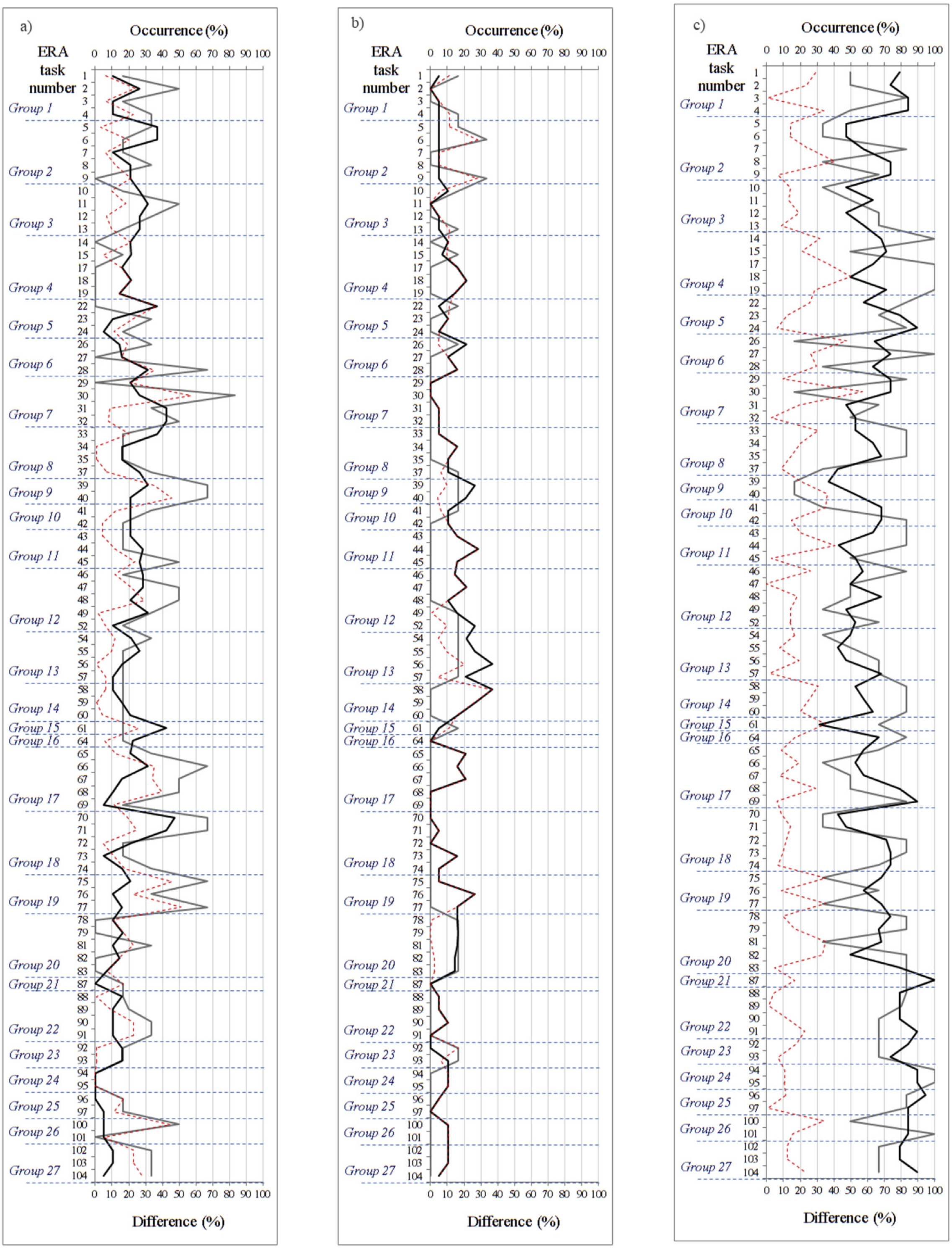

Fig. 4. a–c. A comparison of occurrence proportions (%) between the ENM stress test case study (solid grey lines) and UnISERA (solid black lines) across the 87 validated ERA tasks, for the nature-based uncertainties of a) epistemic, b) aleatory, and c) combined. Difference (%; dashed red lines) is shown on the lower horizontal axis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and 17 ($P = 0.00$). The median agreement between the ENM case study and UnISERA across the three categories of the nature dimension was 26 tasks out of 30 (87%), the lowest of the four ERA phases. Exposure assessment provided UnISERA with the highest severity level of agreement across the four phases for the location dimension, with 27 out of 30 tasks in agreement (90%). The median difference in occurrence rates across all tasks and locations in exposure assessment was 17%, the lowest of the four phases (Fig. S1).

Overall, the median severity level of uncertainty in the ENM case study was 5.0, compared to 4.0 for UnISERA, both in the range of scenario uncertainty. The highest degree of agreement was in risk characterisation and the lowest in exposure assessment, with an overall agreement (across all tasks in the four phases) of 55%. Across 87 tasks, the median difference in the level of uncertainty between comparable values in the ENM case study and UnISERA was just 0.5. Across the 87 tasks, the three categories in the nature uncertainty dimension contributed to a median agreement of 90%, and a median difference in occurrence rates of 12%. The location uncertainty dimension, across its seven categories, yielded a median agreement of 80%. The closest degree of agreement was for the locations of language (98%) and decision (94%), and the lowest for model (58%) and system (71%) uncertainty. Over the four ERA phases, the difference between the values in the ENM case study and the comparable values in UnISERA for the first three case studies was highest for model uncertainty, with a median difference of 45%, with a median difference of 18% seen across all seven locations of uncertainty.

4. Discussion

Where do uncertainties in environmental risk assessments reside? Providing risk analysts with research-informed insight on this might increase the prevalence of uncertainty assessment, the quality of ERAs and the decisions they inform.

4.1. The severity level of uncertainty in UnISERA

To direct resources, environmental risk analysts tackle tasks within preliminary ERAs that are most uncertain, especially where higher tiers of analytical sophistication in the ERA are invoked. In doing so, they conserve precious resources as the ERA becomes more sophisticated, often more quantitative and thus more costly and time-consuming. In UnISERA, these tasks are associated with the primary analysis or evaluation of evidence, rather than its collection or processing. Twelve of the first 20 tasks with the highest severity levels of uncertainty (Table S2; Supporting Information) involved the creation of exposure profiles (tasks 68 and 69), stressor-response profiles (tasks 89 and 90), and the estimation (task 94), aggregation (tasks 96 and 97), or evaluation (tasks 100, 101, 102, 103, and 104) of risk magnitude (Table S2). From an analysis of nine ERAs (six ecological and three human) assessed for the magnitude, reducibility, and quantification of uncertainty, von Stackelberg et al. (2008) found the highest magnitudes of uncertainty were with the selection and implementation of profiling metrics during exposure and effects assessment.

The comparable ERA tasks in UnISERA (65–69 for exposure metrics and 88 to 91 for effects metrics) have higher severity levels of uncertainty associated with them than other tasks within the first three ERA phases. The trend reported by von Stackelberg et al. (2008) is one of increasing uncertainty as one progresses through the four ERA phases; as observed in UnISERA, with median uncertainty severity levels of 3.0 in problem formulation, 4.0 in exposure assessment, 4.3 in effects assessment, and 5.0 in risk characterisation (graphical abstract). The nature category deemed most uncertain was epistemic and aleatory combined; which extends to all tasks for which the nature of uncertainty can be ascribed with confidence. The primary location-based uncertainties were model and extrapolation uncertainties, often occurring in tandem. This is a likely consequence of numerical and statistical models used in exposure and effects assessment, with their need to extrapolate across species and scales (Forbes et al., 2001) to inform exposure and stressor-response profiles (Perry et al., 2010). Model output is used for the estimation and aggregation of risk estimates, the evaluation of which can be subject to stacked uncertainties from aggregated confidence, tolerability, and toxicity thresholds. It is equally important to acknowledge the 'least uncertain' ERA tasks (Refsgaard et al., 2007; van der Sluijs et al., 2004). von Stackelberg et al. (2008) found the lowest uncertainty resided in problem formulation, with which this research agrees, associated with identifying the source(s; analogous to ERA tasks 1, 5, 10, and 11), pathway(s; ERA tasks 3 and 12) and receptor(s; ERA tasks 2, 6, and 13) and their suitable assessment and measurement endpoints (ERA tasks 14, 15, 17, 18, and 19). The primary location-based uncertainty was 'data', connected to the sub-phases of hazard identification and defining the conceptual model (Table 2). Data uncertainty is important in problem formulation, which stresses basing initial ERA tasks on reliable datasets, to ensure the adequacy of tasks and subsequent phases that explore exposures the S-P-R relationships (Wolt et al., 2009).

4.2. The nature and location of uncertainty in UnISERA

The nature of uncertainties is a combination of epistemic and aleatory contributions. Data uncertainty was the dominant location-based uncertainty within UnISERA, with median occurrence rates of at least 50% in all four phases, 13 out of 15 sub-phases, and 69 out of 89 tasks. The highest rates were seen in the sub-phases of preliminary hazard identification in problem formulation, and in collecting stressor, exposure, and receptor information in exposure assessment - both of which are highly reliant on data. Besides being data-driven, the problem formulation phase relies on the implementation of system knowledge for a particular risk and, as such, can be more prone to system-based uncertainty than other phases of an assessment (Wolt et al., 2009; Raybould, 2006). In UnISERA, of the ERA tasks with which system uncertainty was most heavily associated, eight of the first 11 were from problem formulation, specifically the sub-phases of preliminary hazard identification and defining the conceptual model. The latter is susceptible to model uncertainty, though not as much as exposure and effects assessment and risk characterisation, discussed earlier, which accounted for 12 of the first 14 tasks in which model uncertainty featured most heavily. Another location of uncertainty impacting on risk characterisation was language uncertainty; specifically associated with evaluating the significance of a risk using risk criteria and synonymous with the challenges of communicating with, and drawing information from stakeholder groups (Darbra et al., 2008). Generally though, experts believed language uncertainty was of little other concern, perhaps not surprising given the sparse attention attributed to it in the risk literature (Ascough et al., 2008; Regan et al., 2002).

Due to the character of ERAs, which are performed by humans as model representations of environmental systems, natural and human variability are manifest throughout (Huijbregts et al., 2001). Our results suggest specific attention should be paid to the variability inherent to exposure assessment and in evaluating the stressor-response relationship (e.g. effect endpoints) in effects assessment. The other location within the aleatory category, extrapolation, is of key concern during risk characterisation, which is the only example of a location-based concern occurring more frequently in an ERA phase than data uncertainty. Finally, decision uncertainty, though not a large concern according to our experts, was manifest most notably in problem formulation (e.g. considering the relative importance of assessment endpoints to each other; task 24) and risk characterisation (e.g. deciding which assessment endpoints to aggregate into final risk levels; task 96).

4.3. 'Stress-testing' UnISERA for broader application

Despite the debate on how engineered nanomaterials are best assessed (Aschberger et al., 2011; Rocks et al., 2008) the controlling legislation, REACH in the EU and the Toxic Substances Control Act

(TSCA) in the US, recommends accepted ERA methods are applied. In terms of a risk-based approach, the ENM case study was aligned with those tasks in UnISERA, making it applicable for use. For a single-study stress test, it can be more useful to use a case study similar in structure, but different in other ways (González and Herrador, 2007), making the stress test as realistic, testing and as broadly useful as possible. A distinction on the basis of the quantity of empirical evidence available (i.e. established risk vis-à-vis emerging risk) was deemed appropriate.

Of the three uncertainty dimensions, the severity level of uncertainty had the lowest rate of agreement across all 87 tasks at 55%. The ENM case study returned higher severity levels of uncertainty for 53 tasks, UnISERA for 26 tasks, with 8 tasks of equal value. Some disparity in results was expected due to the limited extent to which ENM risks have been researched. For example, ENM exposure assessment, which shared an agreement rate of just 27% with the comparable phase in UnISERA, has little information associated with aspects such as predicted effects concentration (PEC) determination (Quik et al., 2011), fate and behaviour (Gottschalk et al., 2009), and stressor-receptor co-occurrence (Gottschalk and Nowack, 2011). Here is the paradox of using an emerging risk to stress test UniSERA: the stressor is novel and its characteristics, release, and actions on environmental compartments, including receptors, are only partially understood. It follows that the lowest levels of agreement were associated with aspects involving the stressor, and the highest levels were seen for those aspects in which the stressor did not feature. Group 13 tasks, which sought to collect information on the receptor, returned the highest agreement rate across the exposure assessment phase (75%), whilst group 11, collecting information about the stressor's release, and group 14, determining stressor-receptor co-occurrence, yielded rates of 0%. High rates of agreement were not only confined to aspects involving the receptor. Risk characterisation, which draws together the output from the exposure and effects assessment phases, saw an overall agreement of 91% across its contained tasks. The ENM case study also matched UnISERA in terms of its median severity level of uncertainty in this phase, at 5.0. This observation, that uncertainty severity levels can differ greatly between different parts of the same assessment (e.g. between exposure assessment and risk characterisation), supports the view that uncertainties should be first dealt with in the phase in which they occur (Janssen et al., 2004; Refsgaard et al., 2007), rather than leaving uncertainty analysis as a 'bolt-on' task for risk characterisation, with a danger of it becoming an afterthought (Fairman et al., 1998; USEPA, 1998).

4.4. Using UnISERA

We believe that UnISERA can guide environmental risk analysts on the likely locations, natures and severity levels of uncertainties within ERA, which prompts the analyst to prioritise uncertainties in likely settings so they can manage uncertainties better. UnISERA advances existing uncertainty management techniques (UMTs; Knol et al., 2009; Refsgaard et al., 2007; van der Sluijs et al., 2004; WHO, 2008) by guiding analysts in selecting one or more UMTs (Table 3). Table 3 compares uncertainty matrices published elsewhere (Janssen et al., 2004; Refsgaard et al., 2007; van der Sluijs et al., 2004) with updated natures and locations of uncertainty drawn from our typology (WHO, 2008) and with an expanded set of UMTs. Prior to this research, the application of UMTs relied on the ability of the analyst to identify the uncertainties that required managing. UnISERA has reduced that requirement, placing risk analysts in a better position to select one or more UMTs: risk analysts can anticipate which uncertainties exist, and where to expect them throughout their ERAs. An example is Table 4, which combines the 10 ERA tasks (out of 87 tasks in total) with the highest median severity levels of uncertainty within UnISERA, along with the associated natures and locations of uncertainty and appropriate UMTs. The same approach can be followed in assigning UMTs to the remaining 77 ERA tasks in UnISERA (listed in Table S2), or, alternatively, to assign UMTs to the distinct groups of ERA tasks or ERA phases, depending on priorities. We believe this to be a significant step forward.

5. Conclusions and UnISERA limitations

Some caution is required on the claims made herein. In essence, UniSERA has been constructed on the aggregated results of 19 structured elicitations across three risk domains; has been tested by expert risk analysts; and then stress-tested using the emerging risk domain of engineered nanomaterials. Risk characterisation harbours the highest severity levels of uncertainty, with problem formulation the lowest severity levels of uncertainty. A combined epistemic and aleatory category is the dominant nature of uncertainty. 'Data' is the dominant location of uncertainty in problem

Table 3
Appropriate uncertainty management techniques for use in conjunction with different combinations of uncertainty (after Refsgaard et al., 2007; Knol et al., 2009; van der Sluijs et al., 2004; WHO, 2008; Skinner et al., 2014).

Nature→	Epistemic			Aleatory		Combined	
Location→	Data (Availability; Precision; Reliability)	Language (Ambiguity; Under-specificity; Vagueness)	System (Cause; Process; Effect)	Variability (Natural; Human)	Extrapolation (Inter/Intra; Laboratory; Quantity; Spatial; Temporal)	Model (Structure; Output)	Decision
Level↓							
Statistical	CI; EE; LHS; MCS; PDF; SA;	EE; SI;	BBN; EE; SI;	EE; LHS; MCS; PDF;	EE; LHS; MCS; PDF;	BBN; Boot; EE; EP; LHS; MCS; PDF; SeA;	BBN; EE; MCDA;
Scenario	EE; FDC; FL; PBA; SA; ScA;	EE; FL; ScA; SI;	BBN; EE; FDC; ScA; SI;	EE; PBA; UF;	EE; PBA; UF;	BBN; CI; EE; EP; PBA; ScA;	AM; BBN; EE; MCDA; ScA;
Recognised ignorance	EE; FDC; FL; NUSAP; PBA;	EE; FL; SI;	EE; FDC; NUSAP; SI;	EE; PBA; UF;	EE; PBA; UF;	EE; NUSAP; PBA;	EE; PM;

With acronyms corresponding to the UMTs of: AM - Adaptive management[5]; BBN - Bayesian Belief Network[4,5]; Boot - Bootstrapping[5]; CI - Confidence intervals[4,5]; EP - Error propagation[1,2,5]; EE - Expert elicitation[1,2,5]; FDC - Further data collection[5]; FL - Fuzzy logic[3,5]; LHS - Latin hypercube sampling[3,5]; MCS - Monte-Carlo simulation[1,2,3,5]; MCDA - Multi-criteria decision analysis[5]; NUSAP - Numeral, unit, spread, assessment, and pedigree[1,2]; PM - Precautionary management[5]; PBA - Probability bounds analysis[3]; PDF - Probability density function[5]; ScA - Scenario analysis[1,2,4]; SeA - Sensitivity analysis[1,2,3,4,5]; SI - Stakeholder involvement[1,2,4]; UF - Uncertainty factor[5]. Where superscript values denote the sources used to assign UMTs to different uncertainty combinations:1: [78]; 2: [8]; 3: [91]; 4: [12]; 5: [92].

Table 4
Ten ERA tasks with the highest median severity levels of uncertainty within UnISERA and ranked occurrence rates for the nature and locations of uncertainty, including corresponding uncertainty management techniques. The dimensions of uncertainty are shaded green where agreement was observed and red where not. Refer to Table S1 for full descriptors of sub-phase and task group actions.

ERA Task #	ERA Phase	ERA sub-phase	ERA task group	ERA task	Level[a]	Nature[b]	Location(s)[c]	Uncertainty management techniques (UMTs)[d]
72	Effects	Use available evidence to better constrain…	18. (Use available evidence to better constrain…)	Secondary stressors	7.0 (Ig) P=0.48	Co	1: Dat 2a: Sys 2b: Mod 3a: Var 3b: Ext	1: EE, FDC, FL, NUSAP, PBA. 2a: EE, FDC, NUSAP, SI. 2b: EE, NUSAP, PBA. 3a: EE, PBA, UF. 3b: EE, PBA, UF.
101	Risk	Evaluate risk levels	26. Assess confidence in the risk levels using…	Experimental evidence	7.0 (Ig) P=0.02	Co	1: Ext 2a: Dat 2b: Var	1: EE, PBA, UF. 2a: EE, FDC, FL, NUSAP, PBA. 2b: EE, PBA, UF.
76	Effects	Analyse the stressor-response relationship	19. Determine the test dose for the…	Frequency	6.0 (Sc) P=0.89	Co	1: Var 2: Mod	1: EE, PBA, UF. 2: BBN, CI, EE, EP, PBA, ScA.
87	Effects	Integrate multiple LOEs using…	21. (Integrate multiple LOEs using…)	Quantitative methods	6.0 (Sc) P=0.68	Co	1: Mod 2: Dat 3: Var	1: BBN, CI, EE, EP, PBA, ScA. 2: EE, FDC, FL, PBA, SeA, ScA. 3: EE, PBA, UF.
96	Risk	Estimate and aggregate risk	25. Aggregate risk estimates for…	Assessment endpoints	6.0 (Sc) P=0.65	Co	1a: Ext 1b: Mod 2: Var 3: Sys	1a: EE, PBA, UF. 1b: BBN, CI, EE, EP, PBA, ScA. 2: EE, PBA, UF. 3: BBN, EE, FDC, ScA, SI.
97	Risk	Estimate and aggregate risk	25. Aggregate risk estimates for…	Stressors	6.0 (Sc) P=0.55	Co	1: Mod 2a: Sys 2b: Ext 3: Var	1: BBN, CI, EE, EP, PBA, ScA. 2a: BBN, EE, FDC, ScA, SI. 2b: EE, PBA, UF. 3: EE, PBA, UF.
90	Effects	Create stressor-response profile using…	22. Single point methods showing…	Effects levels	6.0 (Sc) P=0.46	Co	1a: Ext 1b: Mod 2a: Dat 2b: Var	1a: EE, PBA, UF. 1b: BBN, CI, EE, EP, PBA, ScA. 2a: EE, FDC, FL, PBA, SA, ScA. 2b: EE, PBA, UF.
94	Risk	Estimate and aggregate risk	24. Estimate risk using…	Single-point profiles	6.0 (Sc) P=0.32	Co	1a: Ext 1b: Mod 2: Var 3: Dat	1a: EE, PBA, UF. 1b: BBN, CI, EE, EP, PBA, ScA. 2: EE, PBA, UF. 3: EE, FDC, FL, PBA, SeA, ScA.
24	Problem	Define the conceptual model	5. Consider the appropriateness of the endpoints	Relative importance of endpoints to each other	6.0 (Sc) P=0.26	Co	1a: Sys 1b: Mod 2a: Var 2b: Ext 3: Dat	1a: BBN, EE, FDC, ScA, SI. 1b: BBN, CI, EE, EP, PBA, ScA. 2a: EE, PBA, UF. 2b: EE, PBA, UF. 3: EE, FDC, FL, PBA, SeA, ScA.
89	Effects	Create stressor-response profile using…	22. Single point methods showing…	Extreme toxicity	6.0 (Sc) P=0.23	Co	1a: Dat 1b: Mod 2: Var 3: Ext	1a: EE, FDC, FL, PBA, SeA, ScA. 1b: BBN, CI, EE, EP, PBA, ScA. 2: EE, PBA, UF. 3: EE, PBA, UF.

[a] Ig=Recognised ignorance; Sc=Scenario uncertainty. Statistical significance (P) is used to rank like values; [b] Co=Combined; [c] Dat=Data; Sys=System; Var=Variability; Ext=Extrapolation; Mod=Model. Median occurrence rates are used to rank like values; [d] BBN - Bayesian Belief Network; CI - Confidence intervals; EP - Error propagation; EE - Expert elicitation; FDC - Further data collection; FL - Fuzzy logic; LHS - Latin hypercube sampling; MCS - Monte-Carlo simulation; NUSAP - Numeral, unit, spread, assessment, and pedigree; PBA - Probability bounds analysis; PDF - Probability density function; ScA - Scenario analysis; SeA - Sensitivity analysis; SI - Stakeholder involvement; UF - Uncertainty factor.

formulation, exposure assessment and effects assessment, followed by variability, system, model and extrapolation uncertainty which is dominant in risk characterisation. The stress testing of UnISERA against the combined results of established ERA risk domains revealed agreement rates of 55%, 90%, and 80% for the severity level, nature and location dimensions, respectively.

This said, our claims of general applicability stand on a selected number of high quality ‘experts’ assessing a large number of UnISERA-ERA based tasks from credible studies and, notwithstanding our desire to statistically represent the data, we have done so on a relatively small number of selected opinions. Further, our desire to secure comparability between studies potentially masks inherent biases between different national philosophies of approach towards ERAs and differences of task understandings within expert fields. For example, consider the uncertainties in reference doses or the purposeful selection of more conservative toxicity data in regulatory assessments; or the gross uncertainty in $\log K_{ow}$ values with implications for risk and remedial decisions (Linkov et al., 2005); or the impact of our aggregation accross different types of risk analysis, say between probabilistic risk studies and qualitative analyses, nowithstanding the weight of analyses that relates to the lines of evidence informing these assessments. Recognising these limitations, we cautiously advance use of UnISERA, as tested here, as a valuable prompt for environmental risk analysts with the use of Tables 3 and 4 especially as a practical tool to guide uncertainty treatment.

Acknowledgements

This research was funded jointly by EPSRC/ESRC/NERC/Defra under grant EP/G022682/1. DJCS was funded by Cranfield University's EPSRC Doctoral Training Accounts EP/P503507/1 and EP/P504147/1. The authors thank the anonymous subject-matter experts who participated in this research.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envpol.2017.02.065.

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